

Towards a natural gesture interface: LDA-based gesture separability

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Abstract

The goal of this paper is to analyse a method of validating a subset of gestures to be used as elements of a HCI interface. We investigate the applicability of LDA for gesture data dimensionality reduction. An Gesture mutual separability analysis of a diverse dataset of 22 natural gestures captured with two motion-capture devices is provided. Fisher criterion is used to produce measures of class separability and class overlap.

Keywords: LDA, gestures, separability, HCI, motion-capture

1. Introduction

With a widespread use of motion-tracking devices, both traditional e.g. computer mouse and new Nintendo Wii RemoteTM, cell phone accelerometer arrays, the importance of motion-based interfaces in Human-Computer Interaction (HCI) systems became unquestionable. The commercial success of simple motion-capture devices led to the development of more robust and versatile acquisition systems, both mechanical e.g. Cyberglove Systems CybergloveTM, Measurand ShapeWrapTM, DGTech DG5VHandTM and optical e.g. Microsoft KinectTM, Asus WAVE XtionTM. Past years brought also an increased interest in the analysis of a human motion itself [10, 11, 1].

While modern motion-capture systems provide accurate recordings of a human body movement, creation of a HCI interface based on acquired data is not a trivial task. The presence of noise in the data as well as its large dimensionality makes them difficult to analyse. Additionally, the hand movement during the execution of a particular gesture, performed by different subjects may vary significantly. Some gestures may become unrecognisable with respect to a particular capturing device.

An human computer interface based on the broad range of natural human gestures, represents the most demanding requirement. But due to the fact that recognition of certain gestures by the computer might be a difficult task, a limited subset of human gestures can be selected by the interface designer.

Simple motion-based interfaces limit their elements to a subset of artificial, well distinguishable gestures or just detection of a presence of body motion.

Therefore, an additional challenge lies in creating an interface based on gestures that are also perceived as natural by users. A choice of a gesture subset for a HCI interface, to be considered natural, should be based on a subjective user convenience of use. However, a developer needs an objective measure of suitability of a gesture for the interface. For a HCI interface element, such measure should be related to a difficulty of gesture classification. It should also be independent from a choice of capturing device and classification method.

Since quality of classification is closely related to the distinctiveness of a classified pattern, this paper considers the problem of finding a gesture separability measure and detection of overlap between gesture classes in the acquired data. In our works we concentrated on hand gestures, captured with two mechanical motion-capture systems. We used a diverse gesture database of twenty two natural gestures performed by a number of participants with varying execution speeds [6].

Looking for a reliable separability measure we decided to use Linear Discrimination Analysis (LDA). While this method has some limitations, particularly regarding similarity of class covariance matrices, it has proved itself to produce good results for many applications including face recognition [13] and speech detection [8].

To reduce an initial dimensionality of the data, Principal Component Analysis (PCA) technique is often employed before performing LDA. However, as suggested by [14], a potential problem lies in an incompatibility of PCA and LDA criterion, when PCA discards dimensions that contain important discriminative information. Since gesture classification is often based on small but significant differences in gesture patterns, we decided to limit the initial data processing to simple, essential operations.

The paper is organized as follows. Section 2 (Related work) presents the selection of works on similar subjects. Section 3 (Method) describes the experiment. Results and charts are presented in Section 4 (Results). Section 5 (Discussion) provides author remarks on the subject, while Section 6 (Conclusion) concludes the research.

2. Related work

In [9], authors provide an analysis of LDA and PCA algorithm with a discussion about their performance for the purpose of object recognition. Authors present results of experiments using a face image database.

In [13], authors use LDA-based feature extraction techniques for face recognition. Authors discuss the problem of a classifier becoming overfitted to the training set which leads to discarding useful discriminative information. An approach using random subspace and bagging is proposed to create a robust face recognition system.

In the paper [12] a motion-capture system based on a data glove, used for dynamic signature verification is described. The technique used by authors is based on Singular Value Decomposition (SVD) and produces an accurate rate of genuine-forgery detection.

Gesture recognition for accelerometer-based motion capture systems is presented in [2]. Authors present an algorithm employed for cell phones. Authors developed a two-stage system consisting of Bayesian networks and Support Vector Machines (SVM) to resolve confusing gesture pairs. Similar problem was described in [3] where the data was preprocessed using PCA to reduce its dimensionality and Hidden Markov Models (HMM) and Dynamic Time Warping (DTW) were employed for data classification.

Thorough analysis of a gesture dataset used in the experiments, along with a discussion on the benefits of naturality of a HCI interface elements, can be found in [6]. PCA analysis of the same dataset together with visualization of eigengestures can be found in [5].

3. Method

The goal of the experiment is to determine a mutual separability for a set of gestures, using Fisher criterion as a separability measure. In the first step, gesture data is projected on a lower-dimensional classification space. Then a mutual separability is determined for every gesture pair.

3.1. Experiment data

A set of twenty-two natural hand gesture classes from 'IITiS Gesture Database' Tab. 1, was used in the experiments. Gestures were recorded with two types of hardware. First one was DGTech DG5VHand^{TM1} motion capture glove [4], containing 5 finger bend sensors (resistance type), and three-axis accelerometer producing three acceleration and two orientation readings. Sampling frequency was approximately 33 Hz. The second one was Cyberglove Systems CyberGlove^{TM2} with a CyberForceTM System for position and orientation measurement. The device produces 15 finger bend, three position and four orientation readings with a frequency of approximately 90 Hz.

During the experiment, each participant was sitting at the table with the motion capture glove on his right hand. Before the start of the experiment, the hand of the participant was placed on the table in a fixed initial position. At the command given by the operator sitting in front of the participant, the participant performed the gestures. Each gesture was performed six times at natural pace, two times at a rapid pace and two times at a slow pace. Gestures number 2, 3, 7, 8, 10, 12, 13, 14, 15, 17, 18, 19, 21 are periodical and in their case the single performance consisted of three periods. The end of data acquisition was decided by the operator.

3.2. Data preprocessing

A motion capture recording performed with a device with m sensors generates a time sequence of vectors $\mathbf{x}_{t_i} \in \mathbb{R}^m$. For the purpose of our work each

¹<http://www.dg-tech.it/vhand>

²<http://www.cyberglovesystems.com/products/cyberglove-ii/overview>

Table 1: The gesture list used in experiments

	Name	Class ^a	Motion ^b	Comments
1	<i>A-OK</i>	symbolic	F	common ‘okay’ gesture
2	<i>Walking</i>	iconic	TF	fingers depict a walking person
3	<i>Cutting</i>	iconic	F	fingers portrait cutting a sheet of paper
4	<i>Show away</i>	iconic	T	hand shoves away imaginary object
5	<i>Point at self</i>	deictic	RF	finger points at the user
6	<i>Thumbs up</i>	symbolic	RF	classic ‘thumbs up’ gesture
7	<i>Crazy</i>	symbolic	TRF	symbolizes ‘a crazy person’
8	<i>Knocking</i>	iconic	RF	finger in knocking motion
9	<i>Cutthroat</i>	symbolic	TR	common taunting gesture
10	<i>Money</i>	symbolic	F	popular ‘money’ sign
11	<i>Thumbs down</i>	symbolic	RF	classic ‘thumbs down’ gesture
12	<i>Doubting</i>	symbolic	F	popular Polish(?) flippant ‘I doubt’
13	<i>Continue</i>	iconic ^c	R	circular hand motion ‘continue’, ‘go on’
14	<i>Speaking</i>	iconic	F	hand portraits a speaking mouth
15	<i>Hello</i>	symbolic ^c	R	greeting gesture, waving hand motion
16	<i>Grasping</i>	manipulative	TF	grasping an object
17	<i>Scaling</i>	manipulative	F	finger movement depicts size change
18	<i>Rotating</i>	manipulative	R	hand rotation depicts object rotation
19	<i>Come here</i>	symbolic ^c	F	fingers waving; ‘come here’
20	<i>Telephone</i>	symbolic	TRF	popular Polish(?) ‘phone’ depiction
21	<i>Go away</i>	symbolic ^c	F	fingers waving; ‘go away’
22	<i>Relocate</i>	deictic	TF	‘put that there’

^a We use the terms ‘symbolic’, ‘deictic’, and ‘iconic’ based on McNeill & Levy [10] classification, supplemented with a category of ‘manipulative’ gestures (following [11])

^b Significant motion components: T-hand translation, R-hand rotation, F-individual finger movement

^c This gesture is usually accompanied with a specific object (deictic) reference

recording was linearly interpolated and re-sampled to $t = 100$ samples, generating data matrices $\mathbf{A}_l = [x_l^{(ij)}] \in \mathbb{R}^{m \times t}$, where l enumerates recordings. Then data matrices were normalized by computing the t-statistics

$$\mathbf{A}'_l = \frac{x_l^{(ij)} - \bar{x}_i}{\sigma_i},$$

where \bar{x}_i, σ_i are mean and standard deviation for a given sensor i taken over all l recording.

Subsequently every matrix \mathbf{A}'_l for was vectorized row-by-row, so that it was transformed into data vector

$$\mathbf{x}_l = [x_l^{(11)}, \dots, x_l^{(m1)}, \dots, x_l^{(1t)}, \dots, x_l^{(mt)}]^T,$$

belonging to \mathbb{R}^p , $p = mt$. Then those data vectors were organized into $n = 22$ classes C_k . Then vectors belonging to each of the classes were horizontally stacked forming the set $\mathcal{G} = \{\mathbf{G}_{C_k} \in \mathbb{R}^{p \times n_k}\}$ of data matrices.

3.3. LDA

Linear Discriminant Analysis — thoroughly presented in [7] — is a supervised, discriminative technique producing an optimal linear classification function, which transforms the data from p dimensional space \mathbb{R}^p into a lower-dimensional classification space.

3.3.1. Two classes

Originally the problem was formulated by Fisher for two-classes in the following form.

Lets consider two set of vectors $\mathbf{x}_l = [x_l^{(1)}, \dots, x_l^{(p)}]^T$, $l = 1, \dots, n$ belonging to two classes $C_k, k = \{1, 2\}$ whose covariance matrices are equal. The goal is to find the vector $\bar{\mathbf{a}} \in \mathbb{R}^p$, that optimally separates these classes. It can be shown that this vector maximizes the equation

$$J_2(\mathbf{a}) = \frac{(\mathbf{a}^T \bar{\mathbf{x}}_2 - \mathbf{a}^T \bar{\mathbf{x}}_1)^2}{\mathbf{a}^T \mathbf{W} \mathbf{a}}, \quad (1)$$

where $\bar{\mathbf{x}}_1$ and $\bar{\mathbf{x}}_2$ denote means for classes C_1, C_2 respectively. \mathbf{W} denotes *within class covariance matrix* calculated in the following way

$$\mathbf{W} = \frac{1}{n-2} \sum_{k=1}^2 (n_k - 1) \mathbf{S}_k,$$

where n is number of all data vectors, n_k is number of data vectors in class C_k and \mathbf{S}_k is the covariance matrix for class C_k calculated from equation

$$\mathbf{S}_k = \frac{1}{n_k - 1} \sum_{\mathbf{x}_i \in C_k} (\mathbf{x}_i - \bar{\mathbf{x}}_k)(\mathbf{x}_i - \bar{\mathbf{x}}_k)^T.$$

It can be shown that $\tilde{\mathbf{a}} \propto \mathbf{W}^{-1}(\bar{\mathbf{x}}_2 - \bar{\mathbf{x}}_1)$. We will call the vector $\tilde{\mathbf{a}}$ the first canonical vector. This vector is a basis of following classification criterion. Given vector \mathbf{x} we classify it to class C_1 if following relation is fulfilled

$$|\tilde{\mathbf{a}}^T \mathbf{x} - \tilde{\mathbf{a}}^T \bar{\mathbf{x}}_1| < |\tilde{\mathbf{a}}^T \mathbf{x} - \tilde{\mathbf{a}}^T \bar{\mathbf{x}}_2|, \quad (2)$$

otherwise we classify it to class C_2 .

3.3.2. Many classes

To find the best separation for k -class problem, when $k > 2$, vector $\tilde{\mathbf{a}}$ should maximize the following equation

$$J_m(\mathbf{a}) = \frac{\mathbf{a}^T \mathbf{B} \mathbf{a}}{\mathbf{a}^T \mathbf{W} \mathbf{a}}. \quad (3)$$

The matrix \mathbf{B} is called the *between-class scatter matrix* and is calculated in the following way

$$\mathbf{B} = \frac{1}{k-1} \sum_{i=1}^k n_i (\bar{\mathbf{x}}_i - \bar{\mathbf{x}})(\bar{\mathbf{x}}_i - \bar{\mathbf{x}})^T,$$

where $\bar{\mathbf{x}}$ denotes aggregated class mean

$$\bar{\mathbf{x}} = \frac{1}{n} \sum_{i=1}^n \bar{\mathbf{x}}_i.$$

The matrix \mathbf{W} is called *within-class scatter matrix*

$$\mathbf{W} = \frac{1}{n-k} \sum_{j=1}^k \sum_{\mathbf{x}_i \in C_j} (\mathbf{x}_i - \bar{\mathbf{x}}_j)(\mathbf{x}_i - \bar{\mathbf{x}}_j)^T,$$

where n is number of all the samples in all the classes.

The eigenvectors of matrix $\mathbf{W}^{-1}\mathbf{B}$ ordered by their respective eigenvalues are called the canonical vectors. It can be proved that the first canonical vector $\tilde{\mathbf{a}}$ of $\mathbf{W}^{-1}\mathbf{B}$ maximizes the expression (3). By selecting first d canonical vectors and forming from them the projection matrix $\tilde{\mathbf{A}}^{(d)} \in \mathbb{R}^{d \times p}$ any $\mathbf{x} \in \mathbb{R}^p$ can be projected onto a lower-dimensional feature space \mathbb{R}^d . This projection separates vectors in classes.

3.4. Gesture separability and overlap

Our goal is to determine gesture class separability and gesture class overlap in function of dimensionality d of the feature space. In order to do so we calculate two sets of coefficients: $\lambda^{(d)}(C_{k_1}, C_{k_2})$ and $\gamma^{(d)}(C_{k_1}, C_{k_2})$ defined below.

3.4.1. Step 1

To reduce the dataset dimensionality, LDA is performed on the dataset \mathcal{G} and matrix $\tilde{\mathbf{A}}^{(d)}$ is calculated.

The dataset \mathcal{G} is projected onto d -dimensional space spanned by first d canonical vectors using matrix $\tilde{\mathbf{A}}^{(d)}$. We obtain transformed dataset $\mathcal{G}^{(d)} = \{\mathbf{G}_{C_k}^{(d)} \in \mathbb{R}^{d \times n_k}\}$, where $\mathbf{G}_{C_k}^{(d)} = \tilde{\mathbf{A}}^{(d)} \mathbf{G}_{C_k}$.

Projection of the data from \mathbb{R}^p onto lower dimensional feature space \mathbb{R}^d decreases the quality of data separation. But at the same time lower dimensional feature spaces are more desirable. Therefore to determine the appropriate value of d we apply following procedure. The family of reduced datasets $\mathcal{G}^{(d)}$, $d = \{1, \dots, p-1\}$ is subjected to LDA algorithm and using the formula from equation (3), the reduced dataset separation measure $\lambda_d = J_m(\tilde{\mathbf{a}})$ is calculated. We look for such value of d that $\lambda_{d+1} - \lambda_d$ is small. After determining appropriate small d_0 we use it in next step.

3.4.2. Step 2

In this step a measure of class separability $\lambda^{(d_0)}(C_{k_1}, C_{k_2})$ is obtained for every pair of distinct classes C_{k_1}, C_{k_2} .

Now the reduced data form the set $\mathcal{G}^{(d_0)}$ are once more a subject to LDA algorithm. For every pair of distinct classes C_{k_1}, C_{k_2} and therefore for every pair of corresponding data matrices $\mathbf{G}_{C_{k_1}}^{(d_0)}$ and $\mathbf{G}_{C_{k_2}}^{(d_0)}$ we calculate class separation measure $\lambda^{(d_0)}(C_{k_1}, C_{k_2}) = J_2(\tilde{\mathbf{a}}^{k_1, k_2})$ equal to the maximized value of linear separation, obtained from equation (1), where $\tilde{\mathbf{a}}^{k_1, k_2}$ is the first canonical vector separating those two classes.

3.4.3. Step 3

In this step a measure of class overlap $\gamma^{(d_0)}(C_{k_1}, C_{k_2})$ is obtained for every pair of distinct classes C_{k_1}, C_{k_2} . The procedure goes as follows: for every pair C_{k_1}, C_{k_2} using the first canonical vectors $\tilde{\mathbf{a}}^{k_1, k_2}$ from the previous step, first calculate $\mathbf{v}_{k_1} = \tilde{\mathbf{a}}^{k_1, k_2} \mathbf{G}_{C_{k_1}}^{(d_0)}$ and $\mathbf{v}_{k_2} = \tilde{\mathbf{a}}^{k_1, k_2} \mathbf{G}_{C_{k_2}}^{(d_0)}$, then calculate

$$\gamma^{(d_0)}(C_{k_1}, C_{k_2}) = \begin{cases} \sup(\mathbf{v}_{k_1}) - \inf(\mathbf{v}_{k_2}) & \text{if } \bar{x}_{k_1} < \bar{x}_{k_2}, \\ \sup(\mathbf{v}_{k_2}) - \inf(\mathbf{v}_{k_1}) & \text{otherwise,} \end{cases}$$

where $\bar{x}_{k_1}, \bar{x}_{k_2}$ are means of $\mathbf{v}_{k_1}, \mathbf{v}_{k_2}$. A value of $\gamma^{(d)}(C_{k_1}, C_{k_2}) > 0$, indicates that classes C_{k_1}, C_{k_2} are not completely separable when projected onto d -dimensional feature space.

4. Results

The results are presented for two devices DG5VHand (DG5) and CyberGlove (CG).

To facilitate gesture dataset processing, in Step 1 of our algorithm, its dimensionality was reduced by projecting the data from \mathbb{R}^p , where $p = 1000$ for DG5 and $p = 2200$ for CG device, onto lower dimensional feature space

	Name	DG5	CG	Summary
1	<i>A-OK</i>	+	-	●
2	<i>Walking</i>	+	+	+
3	<i>Cutting</i>	+	-	●
4	<i>Showe away</i>	-	+	●
5	<i>Point at self</i>	+	-	●
6	<i>Thumbs up</i>	+	+	+
7	<i>Crazy</i>	+	+	+
8	<i>Knocking</i>	+	+	+
9	<i>Cutthroat</i>	-	+	●
10	<i>Money</i>	-	-	-
11	<i>Thumbs down</i>	+	+	+
12	<i>Doubting</i>	+	+	+
13	<i>Continue</i>	-	+	●
14	<i>Speaking</i>	-	-	-
15	<i>Hello</i>	+	+	+
16	<i>Grasping</i>	+	+	+
17	<i>Scaling</i>	+	-	●
18	<i>Rotating</i>	-	+	●
19	<i>Come here</i>	-	-	-
20	<i>Telephone</i>	+	-	●
21	<i>Go away</i>	-	+	●
22	<i>Relocate</i>	+	-	●

Table 2: Concluded separability for gestures: + denotes a separable gesture, - a problematic gesture and ●, a gesture that is problematic for only one of the tested devices.

\mathbb{R}^d . For both devices we calculated normalized class separation value for one-dimensional projection and obtained the very similar results $\lambda_{d=1} \approx 0.9524$. By observing the value of $\lambda_{d+1} - \lambda_d$, we determined that $\lambda_{d=2} - \lambda_{d=1} \approx 0.045$ while $\lambda_{d=3} - \lambda_{d=2} < 0.003$. Further increase of d leads to minimal gain of class separability value. Based on this observation we chose dimension $d_0 = 2$ for the initial projection of data in Step 1.

Projection of the experiment data on \mathbb{R}^2 is presented in Fig. 1. Most of the gestures are well separated. In the majority of visible gesture classes, elements are centred around their respectable mean, with an almost uniform variance. Potential conflicts for small number of gestures may be observed for local regions of the projected data space. The summary of gesture suitability, as an element of a HCI interface, using separability criterion λ was presented in Tab. 2. Gestures were classified as separable, when for C_k , gesture separability $\lambda_{\min} > T_d$, where T_d is an arbitrary value of device separability threshold and λ_{\min} is a minimal value of λ for C_k . In our experiment we took thresholds $T_{DG5} = 0.0004$ and $T_{CG} = 0.0049$.

Tab. 3 presents gesture class pairs, where the value of class overlap $\gamma > 0$. Class overlap was detected for 1.58% of analysed gestures therefore, 81.8% of

Ord.	Device	g_1	g_2	$\gamma_{g_1 g_2}$
1	DG5VHand TM	13	18	2.96×10^{-5}
2	CyberGlove TM	1	14	2.94×10^{-3}
3	CyberGlove TM	5	20	1.58×10^{-3}
4	CyberGlove TM	22	17	4.54×10^{-3}

Table 3: Overlapping gesture pairs ($\{g_1, g_2\} : \gamma_{g_1 g_2} > 0$)

tested classes are completely separable. Small number of conflicts in class data indicates a potential good performance of a gesture classifier based on analysed dataset.

It is not surprising that for devices using optical tapes and accelerometer for data acquisition, high separability of a gesture seems to be associated with an active, fast hand movement eg. *Hello* (15), *Doubting* (12), and repeated use of individual fingers eg. *Walking* (2), *Knocking* (8). Indistinguishable gestures usually employ a wrist movement and unrestricted position of fingers eg. *Show away* (4), *Continue* (13), *Go away* (21).

In Fig. 2 relatively higher separability values for CyberGloveTM can be observed. However, more instances of class overlap was detected for this device. This problem may be related to the arm mount, used to acquire hand movement and orientation readings. While its readings are more precise than DG5VHandTM accelerometer array, the mount slightly restricts arm movement, which results in more cautious gesture performing and may hinder an execution of particular gestures.

5. Conclusion

One of the key requirements of an effective HCI is to allow the user to concentrate on the task that is being carried out, not on the interface elements or interaction mechanics. Actual gesture recognition rate is crucial for this, as recognition errors focus user’s attention on the interaction, and away from the objective. We argue that separability of a gesture is important, yet undervalued measure of its distinctiveness from other patterns, and thus its potential performance.

LDA provides a well documented measure of separability that can be used for choosing a well separable gesture data set for a HCI interface. Despite its limitations Fisher criterion provides satisfactory results for analysis of a motion-capture data.

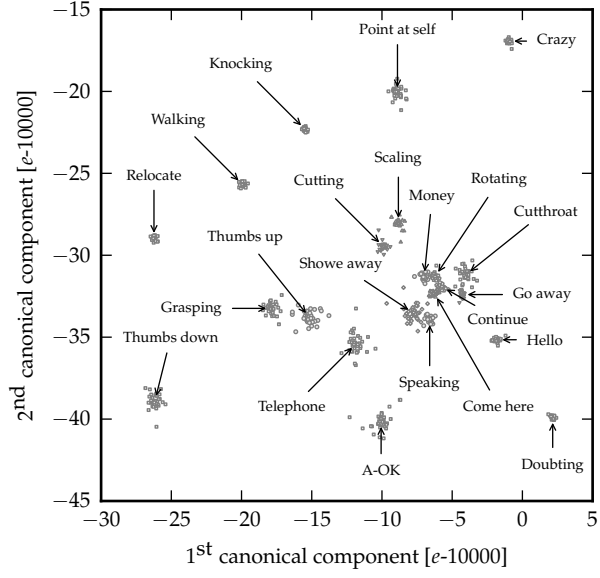
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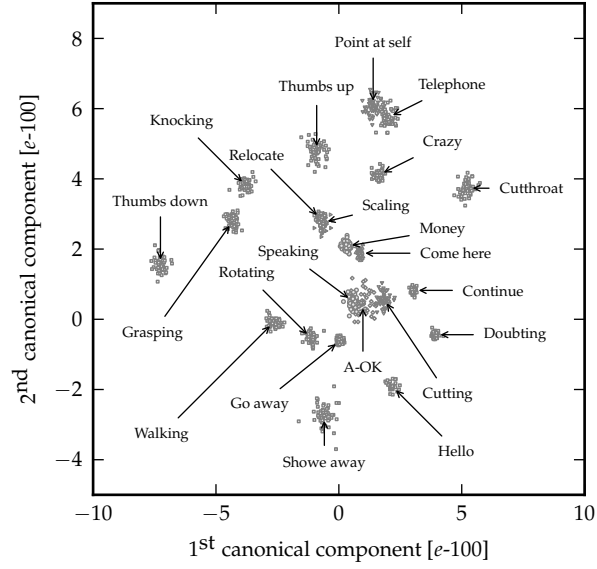
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(a)



(b)

Figure 1: LDA of a dataset \mathcal{G} . The data is projected on $d = 2$ first eigenvectors of $\mathbf{W}^{-1}\mathbf{B}$. Devices: DG5VHandTM(a), CyberGloveTMdata (b).

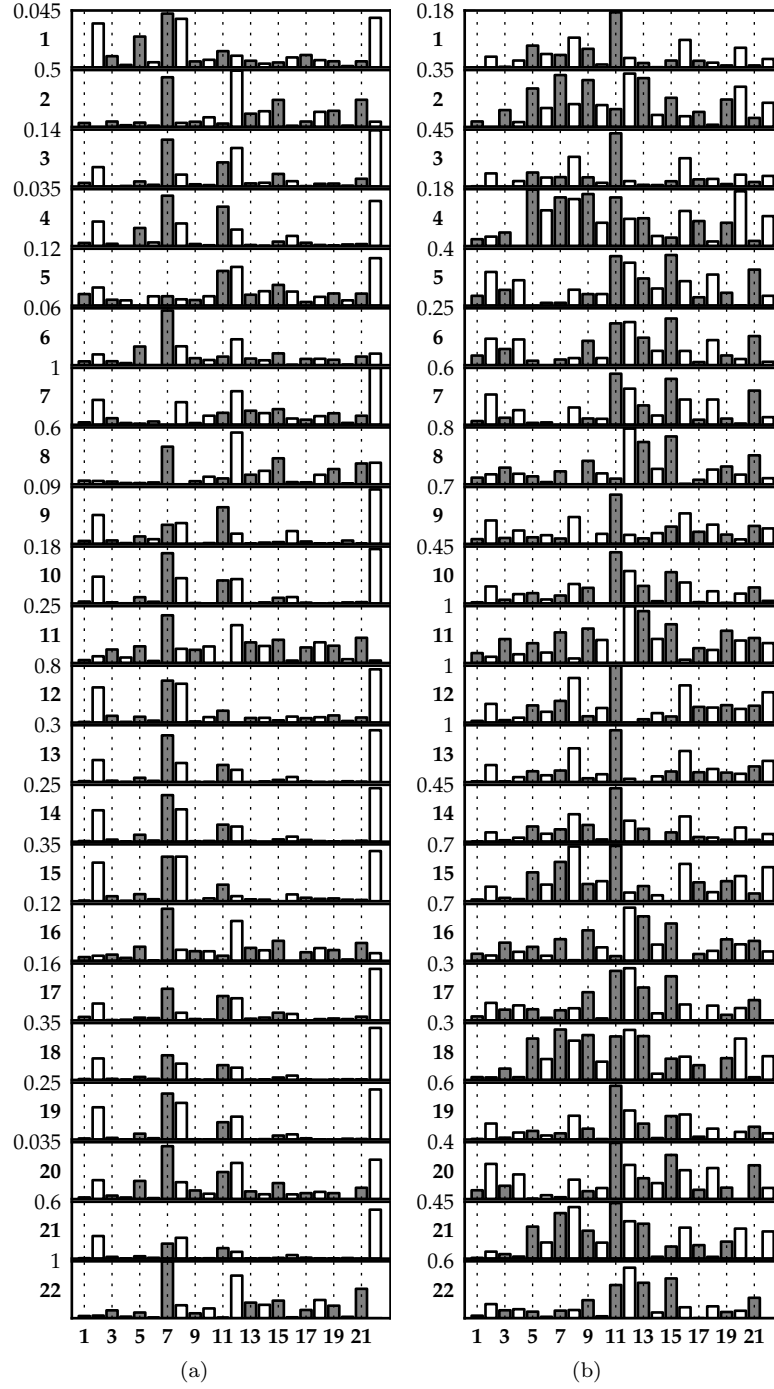


Figure 2: Graphical representation of separability matrix for (a) DG5VHand and (b) Cyberglove. Each plot represents a row of the matrix. Plots are scaled according to maximal value indicated in the upper-left corner of each of the plots. Higher value indicates better separability.